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**RE: Submission of Final Technical Report (Award No.: N00014-05-1-0675)**

To Whom It May Concern:

Attached please find our final technical report on "Developing Autonomous Vehicles that Learn to Navigate by Mimicking Behavior."

Should you have any questions regarding this report, please do not hesitate to contact me. We greatly appreciate your support.

Sincerely,

A handwritten signature in black ink, appearing to read "Dean B. Edwards".

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**Developing Autonomous Vehicles That Learn to Navigate by Mimicking  
Human Behavior**

**FINAL REPORT  
9/28/2006**

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## **Abstract**

A program initiated by the Defense Advanced Research Project Agency (DARPA) called "Learning Applied to Ground Robots" (LAGR) is developing control algorithms that would allow a vehicle to safely travel cross-country. The University of Idaho with funding from the Office of Naval Research is participating in this program in which DARPA provided a vehicle having both sensors and supporting software for the sensors. We used the LAGR vehicle to help solve navigation problems that afflicts both underwater crawlers and ground vehicles. With the application of fuzzy logic and specialized software, we were able to successfully autonomously navigate in an unstructured environment to a specific target or location.



## INTRODUCTION

The surf zone is a very challenging environment for underwater vehicles conducting mine-counter-measures (MCM). A number of different vehicles and methods can be used to identify objects that may be potential mines, including small submarines swimming outside the surf zone, as well as aerial and surface vehicles. Once an object has been identified as a potential mine, a small underwater two-track vehicle, called a crawler, can be used to reacquire and confirm identification, and target the mine. This mission requires the crawler to navigate through difficult terrain to the potential mine object and is similar to the problem of navigating cross-country in an outdoor environment.

DARPA is funding a program called "Learning Applied to Ground Robots" (LAGR) for the purpose of developing control algorithms that would allow a vehicle to safely travel cross-country. The University of Idaho has been selected to participate in this program in which DARPA would supply a vehicle having both sensors and supporting software for the sensors. Because this technology has applications to both ground and underwater vehicles, we proposed that ONR support one graduate student and the maintenance costs for the DARPA vehicle (i.e. \$15K) in order to integrate methods developed at the UI with DARPA's sensors and software to help solve this navigation problem that afflicts both underwater crawlers and ground vehicles.

Researchers at the University of Idaho (UI) proposed to develop a fuzzy logic control system to allow a vehicle to autonomously travel cross-country in an outdoor or underwater environment. This work was based upon a prototype fuzzy logic control system for an autonomous vehicle used in timber harvesting applications that follows an ill-defined trail in an outdoor environment with a limited set of sensors, see previous research vehicles in Figure 1. In the proposed work, we developed a hierarchical fuzzy logic control system where lower level modules will process data and provide recommendations to a supervisory control module. A critical element of the new control system is the Trail Selection Module. This module identifies potential trail segments for the vehicle in both the near and far fields and defines a trail for the vehicle. The system uses visual cues to help identify where potential trail segments are located and attempt to assemble these segments so the vehicle can move toward a location in the far field.

Computer simulations of the robot and its environment, and an optimization process are used to individually train or teach each module. We adapted an ONR developed software package (ALSWE) to simulate the outdoor environment as learned during monthly and semi-annual runs performed at DARPA's facilities. Each module was optimized individually so that if one or more modules should fail, the Supervisory Module in concert with the remaining modules would operate in some optimal manner. The weighting of control recommendations from lower level modules is determined by a *quality factor*. These quality factors allow the supervisory control system to distinguish and prioritize inputs and thus make decisions based upon competing inputs from the lower level controllers. The *quality factors* are also viewed as fuzzy quantities and the control system uses them to "think" about what recommendations are better than others and how to use these recommendations.

Defining a quantitative index for optimizing a module's performance is sometimes difficult. For instance, a vision system provides a large amount of information that can be easily interpreted by a human but cannot be easily interpreted by a control system. Correctly assessing the quality factor of a module in a quantitative manner can also be difficult although, again, an expert operator can many times perform the assessment easily. By utilizing an innovative technique we developed, called *human embedding*, an expert can help generate the metric for training a fuzzy logic system. The performance index is a metric between the expert's responses and the fuzzy logic module's responses. For this procedure to converge, the correct quantities must be observed and the correct logic used. We used experimental data acquired by having a human manually operate a vehicle in typical outdoor environments to help define the correct logic and quantities to observe. We are confident that if a human operator can navigate the robot in the prescribed terrain with only the information available in the FLC system, then we can teach the system to do the same. These methods were used to develop algorithms for the DARPA vehicle shown in Figure 3, which will also be used on the tethered crawler shown in Figure 2.



Figure 1. University of Idaho's Autonomous Test Vehicles

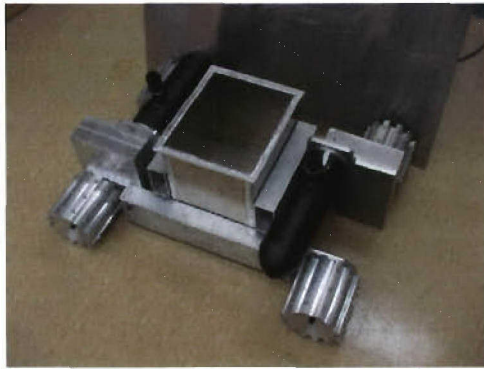


Figure 2. Tethered Crawler



Figure 3. DARPA Vehicle

Recent events have shown the value of using highly automated technology in the battlefield. Autonomous or remote controlled air, terrestrial, and marine vehicles have accomplished important missions while reducing risk to personnel. In the future, as greater numbers of autonomous vehicles are employed, it is hoped that lower

#### **LONG-TERM GOALS**

Use LAGR (Learning Applied to Ground Robots) vehicle to test fuzzy logic obstacle avoidance controller algorithms developed for crawlers in underwater mine countermeasures.

#### **OBJECTIVES**

A number of short-term objectives have been identified to support the long-term goal stated above. They include:

- Develop model of LAGR vehicle in ALWSE-MC (Autonomous Littoral Warfare System Evaluator-Monte Carlo)
- Participate in competitions and learn from other competitors



## APPROACH

The plan was to implement control algorithms from previous University of Idaho projects and adapt an ONR software package to test and optimize the control algorithms for the LAGR vehicle. The existing algorithms are for an autonomous log skidder (ASV30) [1], underwater crawler [2], and vision systems [3]. The autonomous log skidder uses human embedding to train a fuzzy logic controller to follow the same path we expect a human would. The underwater crawler has a hierarchical fuzzy logic control system. In which, a supervisor module takes inputs from a path finding and obstacle avoidance module to determine the heading. The vision system work uses a fuzzy logic system that determines a path segment's membership in slope and roughness fuzzy sets to determine its traversability. The crawler obstacle avoidance has only been used in simulations and the LAGR vehicle was used to test it further.

The ONR software package ALWSE-MC was modified to simulate the LAGR vehicle and the environment. ALWSE-MC is a kinematic, statistical AUV mission simulator that uses point masses to simulate the vehicles. To accurately model the LAGR vehicle and complex 3D environment, changes were made to the simulation. The LAGR vehicle was modeled by defining the vehicle body and sensors (see Figure 6). Next we modified the environment so the vehicle can go through some obstacles (like grass and branches) but stopped by others (like trunks and rocks).

The existing control algorithms were first implemented in the simulation to adjust the parameters for the LAGR vehicle and check for problems in transferring the algorithms across platforms. Then the algorithms were transferred to the University of Idaho LAGR vehicle and further refined for navigating complex environments. The algorithms were installed and run on a similar LAGR vehicle at the DARPA facilities in Figure 4. These tests at the DARPA facilities are monthly competitions among the teams in the project. Since we are joining this project late, our official testing has been minimal and our testing has mainly consists of trial tests on the UI campus.

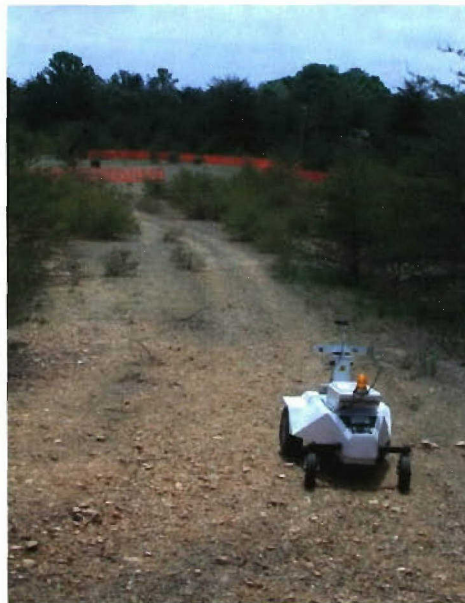


Figure 4. LAGR Vehicle at DARPA Test Facility

## WORK COMPLETED

### 1. Planning

#### 1a. Architecture

##### *Global Path Planning Module*

Our control system was based on the premise that an approximate end-point and suggested route has been defined. The default path will be a straight line from the vehicle's start location to the desired destination. The path definition consists of a series of points that connect the beginning and end of the path. These points are not waypoints the vehicle has to pass through but rather points which define a route based on the topology and traversability of the terrain. The main purpose of the Path Planning Module is that paths may lead toward the destination and avoid local minimums in the path solution. The Path Planning Module also memorizes terrain data from run to run such that performance increases with experience.

##### *Local Trajectory Planning Modules*

A hierarchical fuzzy logic control system was developed to mimic human planning decisions based on the available sensory data and traversability map (see Figure 5). We selected specific functions or control strategies for each low level module. We then established the module's control structure including the input and output variables and the rule base. We parameterized the membership functions of both the input and output variables and selected a performance index for the module. We used computer simulations of the vehicle in the environment to optimize the membership functions' parameters relative to the performance index. All low level modules provide a heading  $\psi$ , quality factor  $Q$ , and speed recommendation. The Supervisor Module uses quality factors to arbitrate the recommendations of the low level modules to obtain a single control recommendation that the robot will use to navigate.

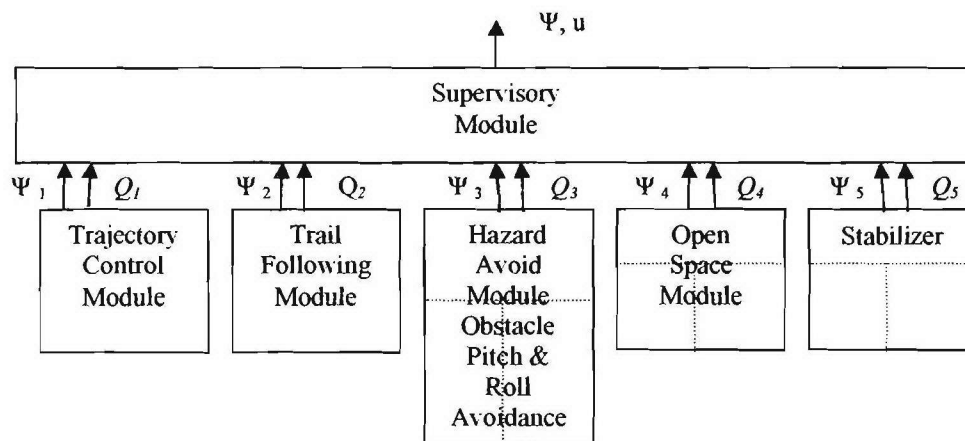


Figure 5. Schematic of Hierarchical Fuzzy Logic Control Structure

The Dead Reckoning Module uses the Local and Global Pose (Position Estimation) to locate the vehicle and determine a control recommendation that attempts to keep the vehicle close to the prescribed path. The Trail Following Module uses a vision system to locate openings and avoid obstacles so as to move through the terrain in the easiest possible fashion. In many instances, the best route may not be along the prescribed path or even back towards the path. In general, the vehicle tries to follow the easiest path, consistent with the path derived by the Global Planner.

The Hazard Avoidance Module uses classical obstacle avoidance techniques [4], INS, GPS and the vision system to detect dangerous terrain and obstacles. The INS is used to prevent the vehicle from rolling over or operating on dangerous slopes. The Hazard Avoidance Module provides a speed and heading goal to the Supervisor Module. The Positional Error Correction Module is a fuzzy inference system that uses image input to check for optical flow and relate this to perceived motion from the INS system and the motor current to check and correct for wheel slip. In addition, a major focus on planner improvement was in correcting for GPS drifts and jumps. With less global positioning error the planner was able to make more accurate decisions with its traversability cost map in all areas of the controller from path planning to trajectory decisions.

The remaining two modules augment the system to correct negative behaviors associated with the base system. The Open Space Module is designed to make the robot steer towards more open areas and thus centers itself on a road or trail. This is to correct for the waypoint paths tendency to closely follow sets of obstacles in minimizing a path distance to the goal. The Stabilizer module is in place to correct for oscillations in the Obstacle Avoidance Module. In certain circumstances, a single object will be in the direct heading of the vehicle. In these cases, the Obstacle Avoidance Module can oscillate between a right and left path around the obstacle. The stabilizer makes the previous heading decision more desirable and thus limits the oscillations.

### ***1b. Simulation and Testing***

We use ALWSE-MC to model the LAGR vehicle for testing and optimize our obstacle avoidance and path planning algorithms before they are implemented on the vehicle. Since ALWSE does not handle vehicle dynamics, a more specific model of the vehicle has been developed. ALWSE-MC models vehicles as point masses; which is not appropriate for modeling the obstacle fields that the LAGR vehicle navigates. The vehicle is modeled as the 70cm x 50cm rectangle in Figure 6, and vehicle center is the position reported by ALWSE-MC. LAGR vehicle sensors are added because ALWSE-MC is designed for underwater vehicles and there are no suitable camera sensors built into the software package. The Bumble Bee stereo system is modeled by returning the closest obstacle within range (marked as X's in Figure 6) for each direction. With this model, the LAGR vehicle can only see the edge of an obstacle and nothing past the first obstacle. There is also a bumper that stops the vehicle during collisions.

The vehicles are supposed to learn the terrain, so that subsequent runs get better results. The vehicle divides the area into 20 cm cells based on the limited accuracy of the stereo vision data. When the stereo camera detects an obstacle, the vehicle marks that cell as impassible, shown with red boxes in Figure 6. The vehicle then uses the marked cell for obstacle avoidance. Figure 7 shows a sample output from the simulations performed on ALWSE-MC.



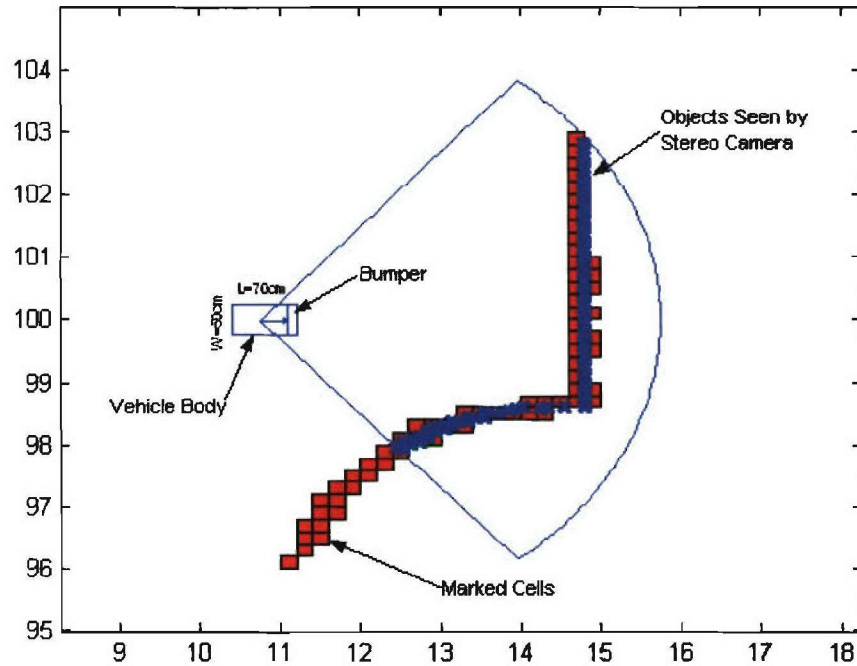


Figure 6. Vehicle Model: *The vehicle is modeled as a 70cm x 50xm rectangle. There is a bumper on the front of the vehicle that stops the vehicle if anything hits it. The stereo system returns the closest obstacle in each direction in the scan area. Once the stereo system picks up an object it marks that cell as impassible in the map.*

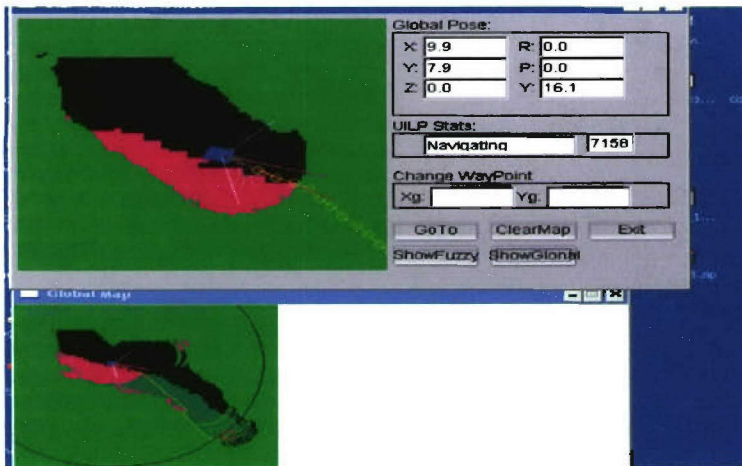


Figure 7. Example Simulation: *Left Image: planner system running with ALWSE-MC. Right Image: 3D simulator display.*

## 2. Perception

Fuzzy Terrain Classifier Module uses stereo data from raw imagery to create two dimensional Cartesian traversability grids (see Figure 8). The current system uses software libraries available onboard the robot to receive and process image pixels into three dimensional arrays of Cartesian points that can then be placed into two dimensional coordinates with features. The features of these grid cells are used as inputs to a fuzzy inference classifier that rates the cells traversability and outputs a ‘likely’ class with associated quality factor.

The linguistic, fuzzy rule base of the classifier is derived through human embedding. Data from feature cells are considered and rules are defined by mimicking a human's choices. The problem with real navigation is that the environment is not always going to have the same types of obstacles and the terrain will vary in color and texture. For this reason the classifier is trained with sets of data to optimize it for the current terrain that it is navigating. This can be done off-line with log data or in real-time as the vehicle is moving through the course. The training data is derived from robot experiences. For example if the robot has successfully traversed a type of cell, then the features within that cell can be considered low cost and traversable. In addition dangerous cells can be marked when contact is made or when the robot becomes stuck. Besides generating a cost function for cells along the terrain the classifier also tries to associate the cell with a particular class of object such as “grass” or “trail” or “tree.” This information is used in the Trail Finding Module in the case where a trail type class is found such that the robot will make an effort to follow this trail towards the goal.

A problem with using traditional stereo machine vision techniques is its short range limitations. A goal of many LAGR teams and UI is to develop long range vision capabilities for use with terrain classification. A method of doing this is to use color in the image to classify pixels that are out of stereo range. This is usually done along the horizon line in the image. Experiments have been conducted on using pixels that are outside of the stereo range as points to be classified and used in the traversability cost map at further ranges. A next step in the development of a more advanced fuzzy inference is to use more complex image processing techniques to find edges and lines in the image space.

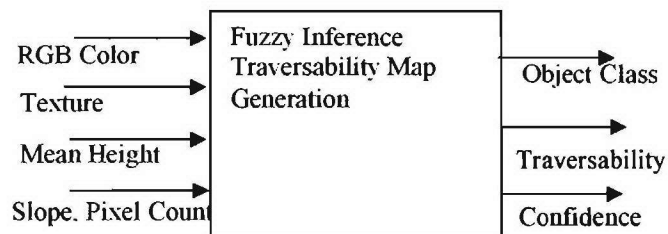


Figure 8. Fuzzy Terrain Classifier Module

## RESULTS

In simulation the vehicle is able to get around solid walls and rocks without collisions. The vehicle is also able to determine what gaps are passable, like between the rocks in Figure 9. It can get through the first set, but it has to go around the second set. During the run, the stereo camera is detecting

obstacles and putting them in the map shown in Figure 10. The vehicle then uses the marked cells to navigate to the goal.

A significant amount of work has gone into image processing of camera sensor data to accurately model the terrain's traversability. This system can be run offline with log data or online with live camera images. The system has already proved to be reliable in varying terrain types and some examples of this are shown in Figure 11.

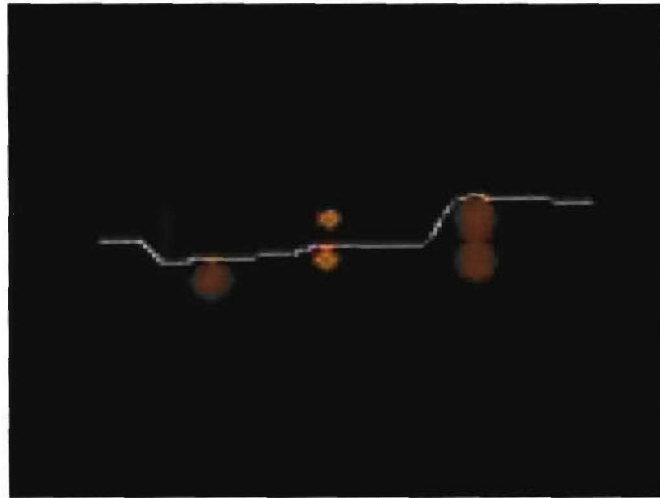


Figure 9. LAGR Run: *In this run the LAGR vehicle navigates its way around walls and rocks. It is able to determine which gaps it can make it through and which ones it cannot.*

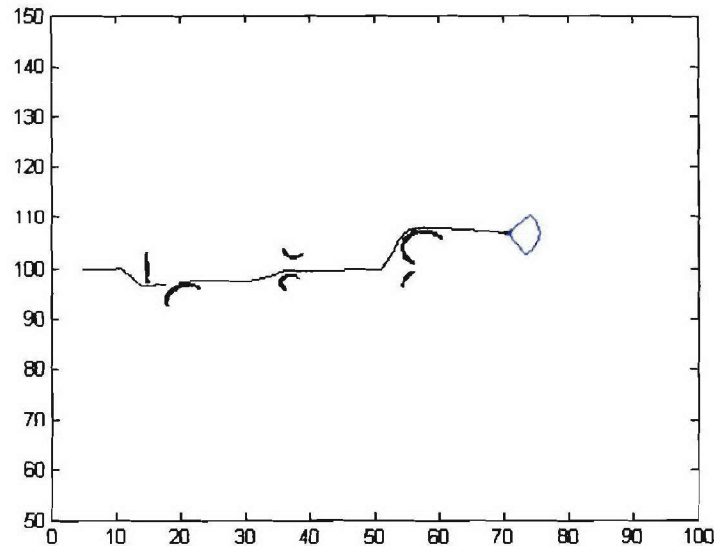


Figure 10. LAGR Map: *The map that the LAGR vehicle developed during the run shown in LAGR Run of Figure 8. The marked cells are all that the LAGR vehicle has for navigation.*



Figure 11. Terrain Perception: *The right image shows raw color data. The middle figure is the same image with masking to show areas of obstacles as classified with the fuzzy logic traversability classifier. The right image is the data projected into a 2 dimensional Cartesian grid that uses magenta to mark dangerous obstacles.*

### **IMPACT/APPLICATIONS**

There is no other group we know of that are currently not using the LAGR baseline system and therefore few teams are using simulation to test and optimize their planner algorithms before uploading them for real time testing. We feel that adapting ALWSE-MC to simulate the LAGR vehicle contributes to the LAGR program by allowing for quicker iterations and tuning of the control algorithms.

By putting our existing algorithms into the LAGR vehicle we can further develop the log skidder control algorithms and test the crawler control algorithms on a real vehicle. The Hierarchical control systems developed for the LAGR vehicle are designed to be modular and general enough to be imported to various autonomous vehicles such that tuning of parameters is minimized and performance is optimized. The human embedding method creates a non-linear, complex controller that closely matches an expert driver's actions. This is of direct interest to ONR's mine counter measure programs where heterogeneous underwater crawlers will be able to use similar software to successfully navigate rocky terrain in an efficient manner.

In addition to the control systems developed, the learning algorithms used to automatically train the vehicle allow the systems to be more robust and adapt to unknown terrain types. This online learning is crucial to successful missions in dynamic underwater environments where communications and endurance are limited.

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